# BIDDING WIND AND SOLAR AS RESERVE PRODUCTS IN US ELECTRICITY MARKETS

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## Abstract

Wind and solar power are two of the world's fastest-growing renewable energy resources. However, forecasting errors and intermittency pose challenges to system operators and limit the use of wind and solar as reserve products. This project developed a stochastic optimization model to determine the optimal offer strategies for wind and solar producers that participate in the day-ahead (DA) and real-time (RT) markets and offer energy and reserve products, including spinning reserves, up regulation, and down regulation. The cost function maximizes the total expected profit while minimizing risk by splitting day-ahead offers between the energy and ancillary service markets. Model outputs include the expected profit in each market in the DA and RT stages and offer curves for each of the four possible products. Case studies are used to verify the model's effectiveness.

## Motivation

Wind and solar resources are currently ineligible to provide ancillary services in US electricity markets, due to their intermittency and high forecast uncertainty. However, to increase the share of energy provided by wind and solar, it may be necessary to use these resources to provide system reserves. Since forecasting errors and intermittency currently limit the use of renewable resources, stochastic optimization, which can consider many different forecast scenarios and formulate an optimal offer given all possible scenarios, is an appropriate tool for calculating optimal energy and reserve offers for renewables. Uncertainty in market prices may affect the producer's offers and should be considered as well. Finally, the risk-aversion level of the producer may impact the offer strategy and should be considered as well.

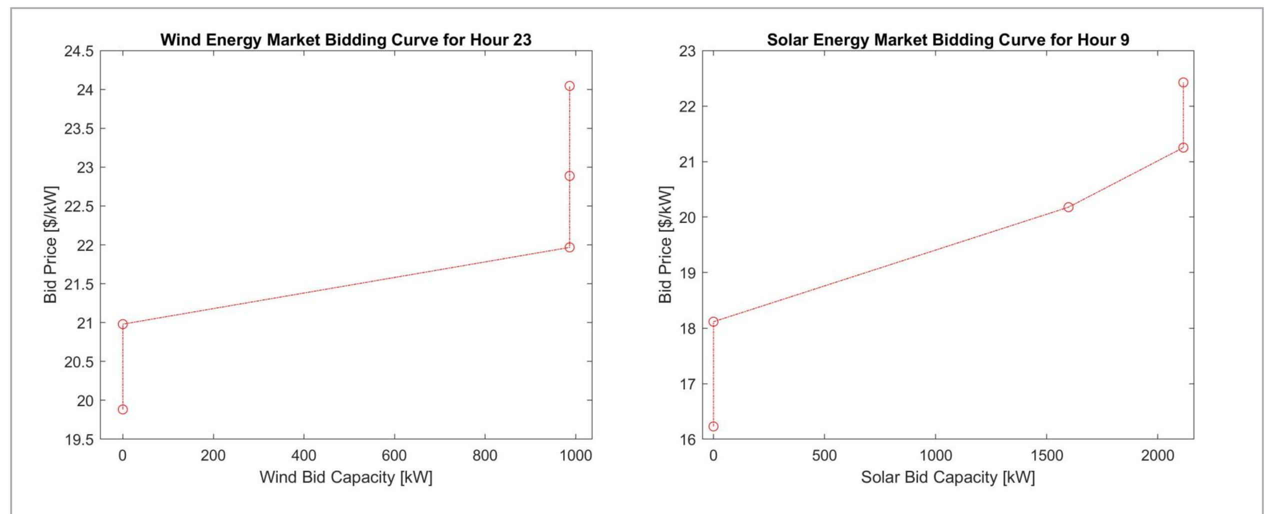


Fig. 1: Examples of offer curves for wind (left) and solar (right). As the DA energy price (y-axis) increases, the amount of wind/solar offered as energy in the DA stage (x-axis) increases.

## Bidding Model

The same stochastic optimization model is used for wind and solar power. The cost function for each hour is optimized over all scenarios $\omega \in \Omega$:

$$max \sum_{\omega=1}^{\Omega} \pi_\omega \{ \lambda_\omega^{DA,E} P_\omega^{DA,E} + \lambda_\omega^{DA,S} P_\omega^{DA,S} + \lambda_\omega^{DA,U} P_\omega^{DA,U} + \lambda_\omega^{DA,D} P_\omega^{DA,D} + \lambda_\omega^{RT,E}(g * P_\omega^F - P_\omega^{DA,E}) + \lambda_\omega^{RT,S}(h * P_\omega^F - P_\omega^{DA,S}) + \lambda_\omega^{RT,U}(u * P_\omega^F - P_\omega^{DA,U}) + \lambda_\omega^{RT,D}(d * P_\omega^F - P_\omega^{DA,D}) \} + \beta \{ \eta + \left(\frac{1}{1-\alpha}\right) \sum_{\omega=1}^{\Omega} \pi_\omega \varphi_\omega \}$$

The first four terms give the expected profit from DA offers of energy/spinning reserve/up regulation/down regulation products, respectively. The next four terms give the expected RT profit or penalty due to deviations from the cleared DA offer. The last term is the Conditional Value at Risk (CVAR). The following parameters are generated using an ARIMA forecasting model:

- $\lambda_\omega^{DA,E}/\lambda_\omega^{DA,S}/\lambda_\omega^{DA,U}/\lambda_\omega^{DA,D}$: DA energy/spinning reserve/up regulation/down regulation prices
- $\lambda_\omega^{RT,E}/\lambda_\omega^{RT,S}/\lambda_\omega^{RT,U}/\lambda_\omega^{RT,D}$: RT energy/spinning reserve/up regulation/down regulation prices
- $P_\omega^F$: forecasted power (wind or solar)

Additional parameters are the probability of each scenario $\pi_\omega$, the weight on the CVAR term $\beta$, and the CVAR quantile α. The CVAR gives the expected profit in the worst (1-α)% of scenarios. The following decision variables are optimized by the model:

- $P_\omega^{DA,E}$ / $P_\omega^{DA,S}$ / $P_\omega^{DA,U}$ / $P_\omega^{DA,D}$: offers of energy/spinning reserve/up regulation/down regulation products in the DA stage
- $g/h/u/d$: fractions of total forecasted power offered as energy/spinning reserve/up regulation/down regulation in the DA stage
- η, $\varphi_\omega$: auxiliary variables used to calculate the CVAR

The model constraints enforce that offer curves must be non-decreasing. In addition, the sum of bids to all markets in the DA and RT stages may not exceed the power forecast in each scenario. We assume that the wind or solar producer's offer is always accepted by the system operator. The model code was written in MATLAB, formulated as a stochastic optimization problem using the free YALMIP toolbox [1] and solved using the linear solver Gurobi [2].

## Case Study

Case studies for wind and solar power are performed to verify the effectiveness of the proposed model. Historical data for generating the price scenarios is obtained from the Southwest Power Pool (SPP) database [3]-[4]. Historical data for wind and solar are obtained from the National Renewable Energy Lab (NREL) databases [5]-[6]. Four months are analyzed to study the impact of seasonal differences on the bidding strategy. The wind and solar producers in the study have capacities of 2 MW and 6 WM, respectively. The weight on the CVAR term $\beta$ is set to 0.1, and the CVAR quantile α is set to 0.95. Fig. 1 shows offer curves generated by the model. Fig. 2 shows the CVAR for wind and solar for each month tested. Higher CVAR corresponds to higher profit in the worst-case scenarios, indicating that June and December are expected to be the most profitable months for solar and wind, respectively. Fig. 3 shows the expected profit by product for solar power, while Fig. 4 shows the same for wind power.

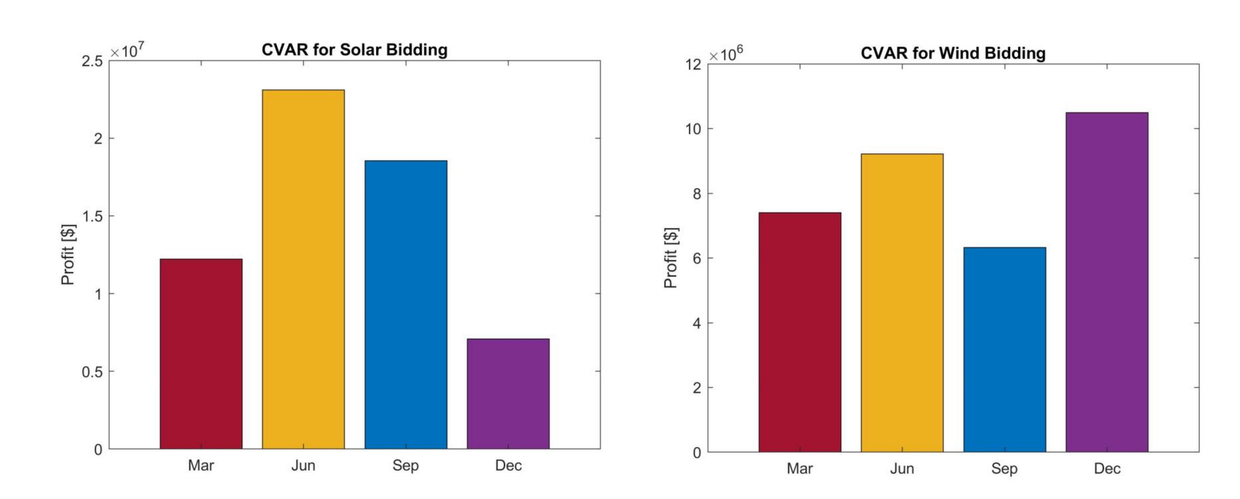


Fig. 2: CVAR for solar and wind bidding.

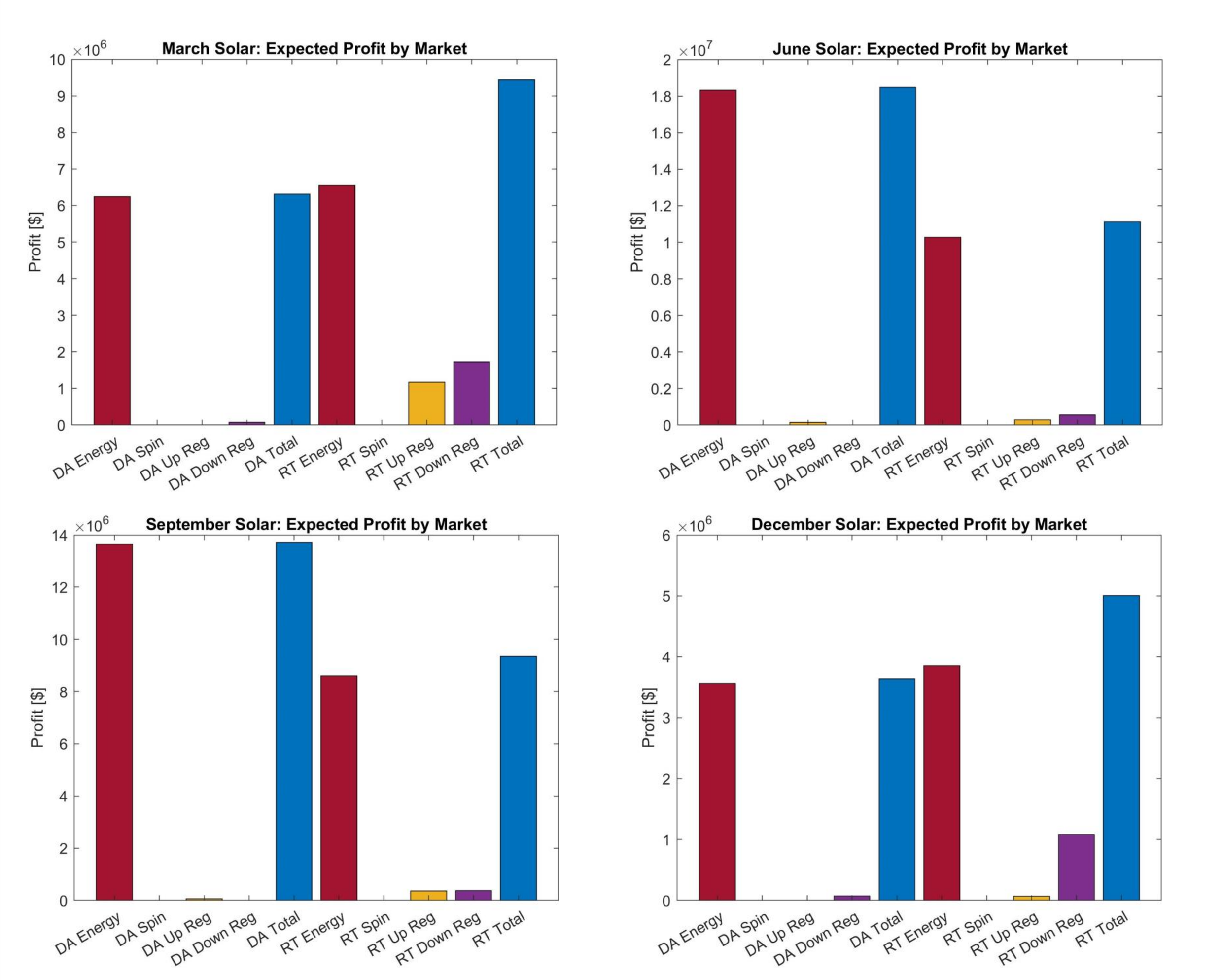


Fig. 3: Expected profit by stage and product for solar power.

## Conclusions

Results of the case study show that most profits come from offering DA/RT energy products. Regulation products are offered occasionally, with the most up and down regulation combined offered in March for both wind and solar. Spinning reserves are rarely offered and could likely be eliminated from future models with minimal change in expected profit. Spinning reserve prices are often the lowest in the DA and RT markets out of the four product types, so it is expected that the wind/solar producer would rarely choose to offer spinning reserves.

The model developed through this project could be useful for public utilities with wind and solar facilities, but limited resources for developing their own bidding models.

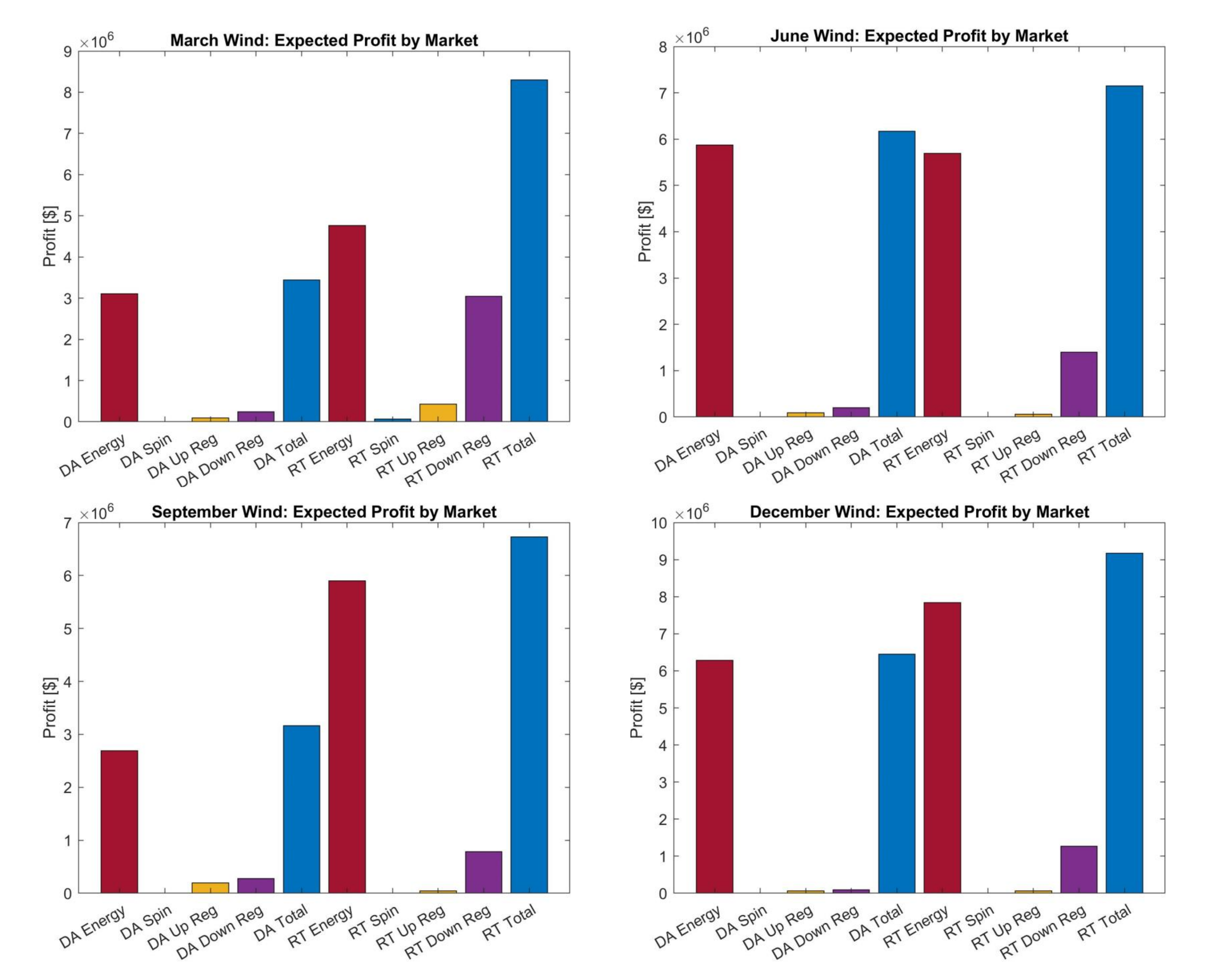


Fig. 4: Expected profit by stage and product for wind power.

References:

[1] J. Lofberg, "YALMIP: A toolbox for modeling and optimization in MatLab," in *Proc. IEEE International Conference on Robotics and Automation*, 2004.

[2] Gurobi Optimization [Online]. Available: https://www.gurobi.com/.

[3] SPPMarket[Online].Available: https://marketplace.spp.org/groups/day-ahead-market.

[4] SPPMarket[Online].Available: https://marketplace.spp.org/groups/real-time-balancing-market.

[5] National Renewable Energy Laboratory (NREL) [Online]. Available: https://www.nrel.gov/grid/wind-integration-data.html.

[6] National Renewable Energy Laboratory (NREL) [Online]. Available: https://www.nrel.gov/grid/solar-power-data.html.

**Please contact astratman5@huskers.unl.edu with questions or requests for the MATLAB code developed in this project.**

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